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Telerobotic Servicing; with Virtual Reality Calibration and Semi-Automatic Intermittent Model Updates

Won S. Kim[1] and Robert Brown[2]

Abstract

A successful commercial implementation of "operator-interactive" VR calibration and recent exciting new developments of semi-automatic VR calibration are described. Computer-vision-assisted VR calibration techniques developed enable semi-automatic intermittent 3-D graphic model update to match the simulated graphics with actual video images. In our

reality calibration that enables semi-automated intermittent model updates using edge-based feature matching.

Figure 1: TELEGRIP 2.4 Video Overlay Option interface

enters the correspondence data between the 3-D object and 2-D image points by clicking corresponding points with a mouse in a graphic simulation window and in a

3. Computer-Vision-Assisted Virtual Reality Calibration

3.1 Detecting Line Segments

[illegible] del data base instead of [illegible] ta of the graphic model [illegible] nsidered invisible when [illegible] nodel was behind the z- [illegible] ad of Canny global edge [illegible] cent 2-D image edges.

3.2 Determining Object Pose by Least-Squares

[illegible] ween 3-D graphic model lines and 2-D video image [illegible] used to determine the object pose (position and [illegible] u, et. al. [9] presented a least-squares algorithm [illegible] hen for the translation. Later, Kumar [8] showed [illegible] ion approach (which he calls R_then_T approach) [illegible] nates in the presense of noisy data than the least- [illegible] otation and translation simultaneously (R_and_T [illegible] he infinite model line algorithm (R_and_T_mod) [illegible] ge line algorithm (R_and_T_img) when extracted [illegible] gments. We selected the R_and_T_mod algorithm [illegible] gles representation is used without involving an [illegible]

3.3 Making Robust Against Outliers

When there are outliers (gross errors) in a given set of correspondence data, the least-squares solution performs poorly, unless outliers are effectively thrown out. Fischer and Bolles [2] presented a technique called RANSAC (random sample consensus) that is robust with respect to outliers. It finds a pose, using a minimum set of three points, and then attempts to grow the solution by successively adding points which are satisfied by the same pose. If a sufficient number of points can be explained by a pose, then it is chosen as the final estimate.

An essentially same concept is used in the "hypothesize-and-test" strategy [1], [4]. It is an iterative two-stage search consisting of hypothesis generation and hypothesis test (verification). In the hypothesis generation stage, a new combination of the minimal or a near minimal number of model-image feature pairs is selected to determine the geometric transformation between the object model and its image. The transformation computed is then used in the hypothesis test stage to project the object model features onto the image and find compatible or aligned image features. The model-image alignment is scored by comparing the transformed model features and image features. The best alignment is the one that maps the most model features onto image features. This two-stage procedure is repeated to find a satisfactory match.

In the edge-based feature matching, the minimum number of model/image edge pairs needed to estimate the geometric transformation is three. However, to reduce the number of ill-conditioned combinations, a combination of four edge pairs, instead of three, is successively tried until a threshold global match score is satisfied. The above edge-based feature matching algorithm implemented is summarized here.

Obtain a list of visible edges of the graphic model by using he model data base and the z-buffer data of the rendered graphic model.

ch visible model edge into 25-pixel line segments, allowing overlap if Apply Hager's local edge detector for each model line segment to find num-strength image line segment in the local rectangular region defined nodel line segment. If the maximum strength is below the threshold s listed as no match. The completed search list shows all the visible ges and their "potential" corresponding image line segments.

3 Hypothesis generation. Select a quadruplet of model and image edge pairs in the search list. In selecting a combination of a quadruplet from the search list, NIL or no-match condition must be included to consider occlusions and noisy edge detections.

4 Hypothesis test. For a selected quadruplet, apply the R_and_T_mod algorithm to compute the object pose transformation. With the obtained transformation, project the object model edges onto the image to find the compatible, aligned image edges. Re-apply the R_and_T_mod algorithm by considering all the aligned image edges. Sum the lengths of all the aligned edge lengths for the model-image alignment score.

5. Repeat the above hypothesize-and-test procedure of Steps 3 and 4 for the search depth levels of 3, 4, and 5. The best match is the one that produces the highest alignment score.

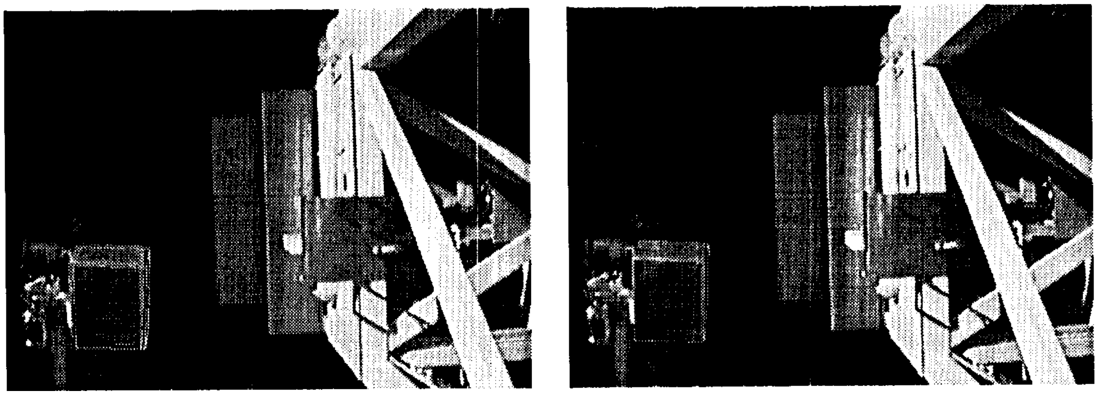
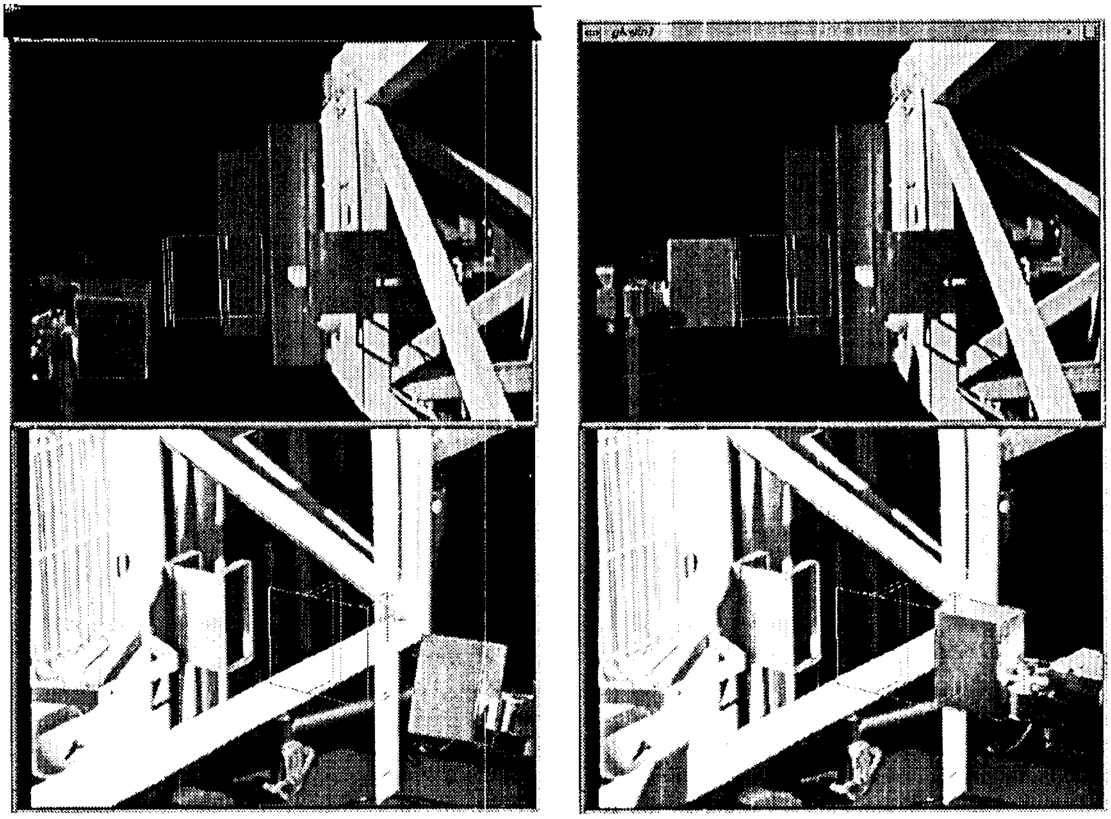


Figure 2: Graphic model overlay before (left) and after (right) edge-based matching.

RPCM (remote power controller module nt unit) insertion task is shown in Figure M-like ORU (rectangular box shape) are ving/monitoring. Before the calibration del and image line segments are apparent. vell aligned.

4. Semi-Automatic Intermittent Model Updates

The above computer-vision assisted VR calibration works well, when there is only one object in the scene with a single-colored background. However, when there are many objects occluding each other, reliable automated matching is still a very difficult problem to solve under the current state of the computer



VR calibration was approximately 1/4 inch. More careful controlled error analysis/experiments are in progress.

The semi-automatic VR calibration with intermittent model updates could open a new way of performing telerobotic servicing. Instead of using a joystick or a hand controller to directly control a remote robot arm, one can use a mouse and a keyboard to interact with a graphics simulation and video overlay to designate the next target position of a robot arm. This new approach may not be as fast as the manual teleoperation for simple tasks, but could enable a much more reliable and accurate telerobotic operation for complex tasks in hazardous environments.

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